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LCA FOR AGRICULTURAL PRACTICES AND BIOBASED INDUSTRIAL PRODUCTS

Reference and functional unit can change bioenergy pathway choices

Sonika Choudhary · Sai Liang · Hua Cai · Gregory A. Keoleian · Shelie A. Miller · Jarod Kelly · Ming Xu

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Abstract
Purpose This study aims to compare the life cycle greenhouse gas (GHG) emissions of two cellulosic bioenergy pathways (i.e., bioethanol and bioelectricity) using different references and functional units. It also aims to address uncertainties associated with a comparative life cycle analysis (LCA) for the two bioenergy pathways.
Methods We develop a stochastic, comparative life cycle GHG analysis model for a switchgrass-based bioenergy system. Life cycle GHG offsets of the biofuel and bioelectricity pathways for cellulosic bioenergy are compared. The reference system for bioethanol is the equivalent amount of gasoline to provide the same transportation utility (e.g., vehicle driving for certain distance) as bioethanol does. We use multiple reference systems for bioelectricity, including the average US grid, regional grid in the USA according to the North American Electric Reliability Corporation (NERC), and average coal-fired power generation, on the basis of providing the same transportation utility. The functional unit is one unit of energy content (MJ). GHG offsets of bioethanol and bioelectricity relative to reference systems are compared in both grams carbon dioxide equivalents per hectare of land per year (g CO_2-eq/ha-yr) and grams carbon dioxide equivalents per vehicle kilometer traveled (g CO_2-eq/km). For the latter, we include vehicle cycle to make the comparison meaningful. To address uncertainty and variability, we derive life cycle GHG emissions based on probability distributions of individual parameters representing various unit processes in the life cycle of bioenergy pathways.
Results and discussion Our results show the choice of reference system and functional unit significantly changes the competition between switchgrass-based bioethanol and bioelectricity. In particular, our results show that the bioethanol pathway produces more life cycle GHG emissions than the bioelectricity pathway on a per unit energy content or a per unit area of crop land basis. However, the bioethanol pathway can offer more GHG offsets than the bioelectricity pathway on a per vehicle kilometer traveled basis when using bioethanol and bioelectricity for vehicle operation. Given the current energy mix of regional grids, bioethanol can potentially offset more GHG emissions than bioelectricity in all grid regions of the USA.
Conclusions The reference and functional unit can change bioenergy pathway choices. The comparative LCA of bioenergy systems is most useful for decision support only when it is spatially explicit to address regional specifics and differences. The difference of GHG offsets from bioethanol and bioelectricity will change as the grid evolves. When the grids get cleaner over time, the favorability of bioethanol for GHG offsets increases.

Keywords Bioelectricity · Bioethanol · Functional unit · Life cycle · Reference system · Switchgrass

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1 Introduction

Driven by increasing demand for alternative energy sources and rising concerns on climate change mitigation through reducing greenhouse gas (GHG) emissions, biomass-based energy (bioenergy) has experienced rapid development in the last decade. Bioenergy derived from cellulosic feedstocks (non-food-based feedstocks including crop residues, wood residues, dedicated energy crops, and industrial wastes) is particularly promising for increasing renewable energy supply and reducing GHG emissions (Carroll and Somerville 2009; Liang et al. 2012).

Cellulosic biomass can be converted into two more usable forms of energy: liquid fuels (e.g., bioethanol) or electricity. In the USA, cellulosic biofuel development is strongly supported by the current government policies. The Renewable Fuel Standard (RFS) mandates the production of biofuels to reach 36 billion gallons per year by 2022, with 21 billion gallons from cellulosic and other advanced biofuels (i.e., biofuels other than derived from corn starch or other food crops) (US EPA 2012). On the other hand, state governments have established Renewable Portfolio Standards (RPS) to promote electricity generation from renewable sources, including biomass (bioelectricity) (DSIRE 2012). It is estimated that the potential market value of bioelectricity will reach $53 billion by 2020 (Pike-Research 2010).

These two cellulosic bioenergy pathways generate different life cycle GHG emissions. Life cycle analysis (LCA) studies have separately measured life cycle GHG emissions of cellulosic biofuels (e.g., Bessou et al. 2011; Fu et al. 2003; Hill et al. 2006; Liang et al. 2012; Uihlein and Schebek 2009; Kumar and Murthy 2012; Bai et al. 2010) and bioelectricity (e.g., Heller et al. 2003; Mann and Spath 1997; Luk et al. 2013). However, what is more relevant to policy making is to compare these two pathways under the same system boundary and same assumptions. To date, only a few studies have conducted comparative life cycle GHG analysis for the two cellulosic bioenergy pathways. Campbell et al. found that bioelectricity can power approximately 81 % more transportation mileage and produce an average of 108 % more GHG emissions offsets than cellulosic ethanol on a per unit area of cropland basis (Campbell et al. 2009). Rowe et al. also found, on a per unit energy content basis, the cellulosic biofuel pathway resulted in more life cycle GHG emissions and fossil energy inputs than the pathway of producing heat and power using cellulosic biomass (Rowe et al. 2011).

While bioelectricity seems to offer more life cycle GHG offsets than cellulosic biofuels do, these studies only compare particular aspects of these two bioenergy pathways due to the selection of functional units. In particular, Campbell et al. (2009) only compare these two pathways on a per unit area of cropland basis, while Rowe et al. (2011) choose energy content of the final products as the comparison basis. Neither of them compares these two pathways based on the actual functions of biofuels and bioelectricity. For biofuels, the primary function obviously is to provide transportation utility. However, functions of bioelectricity are more complex due to the fact that bioelectricity generation will most likely be connected with the grid. Thus, bioelectricity could be used for many more purposes than charging batteries for electric vehicles (EVs) as studied in Campbell et al. (2009). In addition, the GHG offsets from bioelectricity largely depend on the regional energy mix on the grid; but such grid-dependent GHG offsets are not well quantified.

Moreover, inherent uncertainty and variability exist in LCA, which pose significant challenges to the interpretation of LCA results for decision support (McKone et al. 2011). While quite a few recent studies have discussed the uncertainty and variability in LCA of biofuels (e.g., Campbell et al. 2009; Mullins et al. 2011; Stratton et al. 2011; Whitaker et al. 2010) and bioelectricity (e.g., Campbell et al. 2009; Johnson et al. 2011) individually, to our knowledge, there are no published studies examining the uncertainty and variability associated with a comparative LCA of the biofuel and bioelectricity pathways for cellulosic bioenergy. Such kinds of studies can provide significant additional information for policy making on cellulosic bioenergy.

In this paper, in order to address the two research needs noted above, we present a comparative and stochastic life cycle GHG analysis of the biofuel and bioelectricity pathways for cellulosic bioenergy. We use an attributional LCA approach in this study to address the impacts due to the production of biofuel and bioelectricity instead of considering indirect effects arising from changes in the outputs of biofuel and bioelectricity (Brander et al. 2008). We quantify the life cycle GHG emissions of each pathway, comparing with reference fossil-based energy systems at the regional level likely to be displaced by either biofuels or bioelectricity. To address uncertainty and variability, we derive the life cycle GHG emissions based on probability distributions of individual parameters representing various unit processes in the life cycle of bioenergy pathways. Given that cellulosic biofuels and bioelectricity production compete with each other for limited supply of land and biomass, this research is directly relevant to bioenergy policy-making in the USA.

Analysis in this research focuses on bioethanol and bioelectricity derived from switchgrass. As a perennial grass native to North America, switchgrass is widely considered as a popular candidate crop for the cellulosic ethanol production under the RFS and can be used to generate electricity at the utility scale by direct firing or gasification process (McLaughlin and Kszos 2005). The comparative and stochastic life cycle GHG analysis framework for different bioenergy pathways will be generally applicable to other cellulosic sources such as willow plant or corn stover.

2 Methods and data

2.1 System boundary

As shown in Fig. 1, the system boundary of this study includes agricultural inputs for switchgrass cultivation, feedstock collection and transportation, production, distribution, and end use. We assume that switchgrass feedstock is converted into electricity through integrated gasification combined cycle (IGCC). Fossil-based energy usage and GHG emissions are accounted for in each stage within the system boundary. Other environmental impacts are not covered in this study, which represent an important research avenue in the future to avoid shifting environmental impacts from one to another (Liang et al. 2012, 2013; Yang et al. 2012). Although CO_2 emissions from biomass combustion can potentially have relatively significant contribution to global warming (Cherubini et al. 2011), we assume carbon neutrality for bioenergy production for simplicity in this study. In particular, usable form of energy is generated using a feedstock (switchgrass) which is grown specifically for this purpose. The carbon sequestered in switchgrass growth offsets the carbon emissions from bioethanol combustion or biomass combustion for power generation. We account for the difference between EVs and liquid fuel-powered vehicles in this study based on the literature results. Indirect land use change (ILUC) impacts are important in bioenergy LCA (Chamberlain et al. 2011; Mathews and Tan 2009; Plevin et al. 2010; Rowe et al. 2011; Sanchez et al. 2012; Hertel et al. 2010; Kløverpris et al. 2008, 2010; Searchinger et al. 2008; Tonini et al. 2012; Vázquez-Rowe et al. 2013; Reinhard and Zah 2011). However, this study conducts the LCA from an attributional perspective, which only considers direct impacts in different parts of the life cycle (Brander et al. 2008). Moreover, GHG emissions from ILUC will be the same per hectare of switchgrass regardless of ultimate end use. We hence do not account for GHG emissions associated with ILUC in this study. Detailed information regarding assumptions made for this study can be found in the Electronic Supplementary Material.

2.2 Reference system

The reference system refers to a fossil fuel alternative to which bioenergy is compared. Energy from bioethanol has a different utility than energy from electricity. Bioethanol helps with meeting the demand of alternative fuels for the transportation sector, whereas bioelectricity helps in reducing the fossil fuel consumption in the electric power generation. We consider the savings in GHG emissions of bioenergy systems from the displacement of fossil fuels along particular pathways. Based on this criterion, it becomes important to quantify the life cycle GHG emissions impacts of each pathway as compared to the reference case—the fossil energy system. A reference case energy system is chosen that is realistically likely to be displaced by the particular bioenergy system. In the case of cellulosic bioethanol in the USA, it is most likely to replace gasoline use in internal combustion engine vehicles. Hence, the reference system chosen for cellulosic bioethanol is the equivalent amount of gasoline that provides the same transportation utility as cellulosic bioethanol does. Choosing a reference system for bioelectricity is more complex. Bioelectricity is most likely to replace average grid electricity in a region. However, the environmental profiles of grid electricity vary from region to region due to different energy mix for power generation. In this research, we use multiple reference systems for bioelectricity, including the average US grid, regional grid in the USA according to the NERC, and average coal-fired power generation. More details on the reference system can be found in the Electronic Supplementary Material.

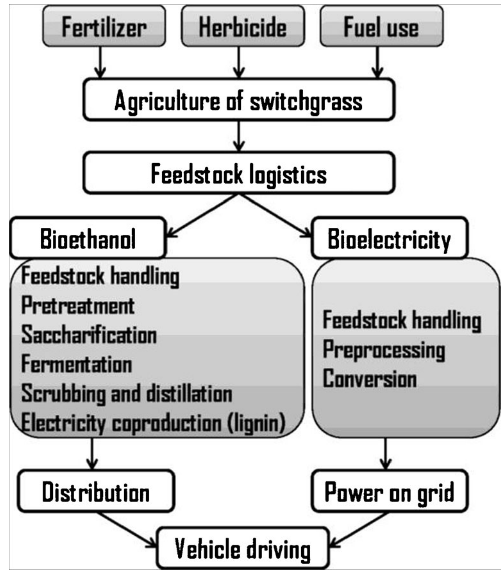

Fig. 1 System boundary of comparative life cycle GHG analysis for switchgrass-based bioenergy pathways in this study

2.3 Functional unit

The life cycle GHG emissions from the bioethanol pathway are expressed in grams carbon dioxide equivalents per megajoule of energy output (g CO_2-eq/MJ). The lower heating value (LHV) of bioethanol is used to convert it from volumetric units to megajoule. Using megajoule instead of volumetric units makes it easy to compare bioethanol with its fossil-based counterpart, gasoline system, as well as bioelectricity life cycle GHG analysis results of which are also expressed on a per unit energy content (MJ) basis. It is a convenient unit to compare bioelectricity with other reference electricity systems such as the US grid average, regional grids, or coal-fired power plants. GHG offsets of bioethanol and bioelectricity relative to reference systems are compared in both grams carbon dioxide equivalents per hectare of land per year (g CO_2-eq/ha-yr) and grams carbon dioxide equivalents per vehicle kilometer traveled (g CO_2-eq/km). For the latter, the vehicle cycle is included in the system boundary to make the comparison meaningful. More details on the functional unit can be found in the *SI*.

2.4 Comparison of greenhouse gas offsets per hectare of land

The comparison of GHG offsets per hectare (ha) of land is formulated to indicate GHG offset potentials in terms of land use efficiency or GHG offset potentials from a unit area of cropland. The reference system for the bioethanol pathway is gasoline, while the references for the bioelectricity pathway are the US average grid and coal-fired power generation. We assume that all the switchgrass produced in a year from a hectare of land is either used to produce ethanol or electricity.

2.5 Comparison of greenhouse gas offsets per vehicle kilometer of travel

Comparison of GHG offsets per vehicle kilometer (km) of travel is formulated assuming that all the biomass is used only for powering the transportation sector. We assume that bioelectricity is used to charge EVs, and bioethanol is used to power flex fuel vehicles (FFVs). We account for both the fuel cycle and vehicle cycle GHG emissions in this comparison.

2.6 Monte Carlo simulation to address uncertainty

Instead of using single average values for input parameters in the life cycle GHG analysis, we define a domain of possible values using probability distributions for each parameter. We then use Monte Carlo simulation (100,000 samples) to generate random inputs from the probability distributions defined for each parameter, perform deterministic computation on the inputs, and aggregate the results (Hung and Ma 2009). These parameters are assumed to be independent of each other for simplicity given the focus of this research on reference systems. Addressing the interdependence of key parameters (e.g., switchgrass yield and herbicide application rate) in future research can potentially change the result of the comparative life cycle GHG analysis; however, the importance of selecting the right reference system remains valid. The MATLAB software is used to perform these simulations. The total life cycle GHG emissions are the sum of the emissions at each stage.

2.7 Data sources

To obtain probability distributions of input parameters for Monte Carlo simulations, we examined a variety of data sources to derive the means and variations for each parameter. We develop probability distributions for parameters following Binkman et al. (2005). All input parameters are assumed to follow normal distributions or triangular distributions with adjustment for unrealistic results (e.g., negative values), which are detailed in the Electronic Supplementary Material. Data for the agriculture phase are obtained from the studies of Davis et al. (2008), Groode (2008), and Johnson et al. (2011). Table S1 in the Electronic Supplementary Material summarizes the mean and standard deviation values of major LCA input parameters in the switchgrass agricultural phase. Fig. S1 (Electronic Supplementary Material) shows the probability distribution for switchgrass yield used in our analysis. We use the integrated biomass supply analysis and logistics (IBSAL) model to estimate the energy use and GHG emissions associated with switchgrass collection and transportation logistics (Kumar and Sokhansanj 2007). Data for the cellulosic bioethanol production process are obtained from the studies of Humbird et al. (2011) and MacLean and Spatari (2009) based on a detailed technical process design. Fuel economy data for vehicle driving using gasoline, bioethanol, and electricity are acquired from West et al. and the Department of Energy (DOE 2012; West et al. 2007). Conversion efficiencies for biomass to electricity are assimilated from existing deployed bioelectricity power plants (Bessou et al. 2011; Brown et al. 2009; Peterson and Haase 2009). Appropriate GHG emission factors are taken from the Greenhouse gases, Regulated Emissions, and Energy use in Transportation (GREET) model 1.8 version (ANL 2012). Vehicle cycle GHG emissions are from Hawkins et al. (2013). In addition, feedstock logistics and biorefinery chemical uses are poorly documented in literature given the huge regional variations. We have reviewed the most recent literature and referred to the most relevant data sources. Detailed information regarding data sources and derived probability distributions for life cycle GHG analysis parameters can be found in the Electronic Supplementary Material.

3 Results

3.1 Life cycle greenhouse gas emissions

Our results complement Campbell et al. (2009) and confirm with Rowe et al. (2011) that the life cycle GHG emissions of the switchgrass-based bioethanol pathway are generally higher than those of the bioelectricity pathway on a per unit energy content basis (Fig. 2a). Delivering 1 MJ worth of bioethanol derived from switchgrass on average produces 7.1 g CO_2-eq GHG emissions more than delivering 1 MJ worthy of bioelectricity, ranging from 1.4 to 12.4 g CO_2-eq. The probability distributions of the life cycle GHG emissions for switchgrass-based bioethanol and bioelectricity pathways are both skewed to the right (Fig. S5, Electronic Supplementary Material). These right-tailed distributions lead to the left-tailed distribution of the difference between bioethanol and bioelectricity in the life cycle GHG emissions (Fig. S6, Electronic Supplementary Material). It suggests that, under highly unlikely circumstances (left tail in Fig. S4, Electronic Supplementary Material), producing bioelectricity using switchgrass as the feedstock could generate slightly more life cycle GHG emissions than producing bioethanol could.

Figure 2b shows the life cycle GHG emissions of the bioethanol pathway by different processes including switchgrass agriculture, feedstock logistics, biorefinery, and ethanol distribution. The average life cycle GHG emissions are 35.6 g CO_2-eq/MJ of energy delivered, ranging from 26.8 to 52.5 g CO_2-eq/MJ. This result is comparable with the previous studies on the life cycle GHG emissions of cellulosic ethanol (e.g., Campbell et al. 2009; Farrell et al. 2006). Switchgrass agriculture, feedstock logistics, and biorefinery contribute approximately 31, 37, and 27 % of the life cycle GHG emissions. Notably, the switchgrass agriculture process among all processes contributes the most variation to the life cycle emissions. To measure the feasibility of bioethanol in terms of net energy gain, we use energy return on investment (EROI), a ratio of the amount of usable energy delivered in particular energy product to the amount of nonrenewable energy inputs required to produce the product. The EROI of switchgrass-based bioethanol is on average 4.1 MJ_{output}/MJ_{input}, ranging from 2.4 to 5.4 MJ_{output}/MJ_{input} (Fig. S7, Electronic Supplementary Material).

Figure 2c shows the life cycle GHG emissions of the bioelectricity pathway by different processes including switchgrass agriculture and feedstock logistics. The average life cycle GHG emissions are 28.4 g CO_2-eq/MJ, ranging from 16.5 to 48.8 g CO_2-eq/MJ. The switchgrass agriculture and feedstock logistics contribute approximately 46 and 54 % of the life cycle GHG emissions, respectively. The variation of the life cycle GHG emissions predominantly comes from the variation of emission in the switchgrass agriculture phase. The EROI of switchgrass-based bioelectricity is lower than that of bioethanol, ranging from 1.9 to 4.9 MJ_{output}/MJ_{input} with the mean of 3.5 MJ_{output}/MJ_{input} (Fig. S7, Electronic Supplementary Material).

The switchgrass agriculture process contributes most variations to the life cycle GHG emissions of both bioethanol and bioelectricity. Figure 2d breaks down GHG emissions from the switchgrass agriculture process according to sources of emissions. On a per unit area of cropland basis, GHG emissions for switchgrass agriculture are on average 856 kg CO_2-eq/ha-yr, ranging from 353 to 1,549 kg CO_2-eq/ha-yr. Our results are comparable with the previous estimate (971 kg CO_2-eq/ha-yr) by Farrell et al. (Farrell et al. 2006), but also provide the variation of results due to parameter variability. Energy use in producing and transporting nitrogen fertilizer (Fig. S6, Electronic Supplementary Material) and direct N_2O emissions contribute approximately 32 and 58 % to the total GHG emissions from switchgrass agriculture, respectively. Notably, these two processes also contribute most variations to the total GHG emissions in the agriculture phase.

3.2 Emissions offsets under different reference systems and functional units

The comparison of life cycle GHG emissions of switchgrass-based bioenergy implies that the bioethanol pathway generally produces more GHG emissions than the bioelectricity pathway does on an energetic basis. However, the quality of energy is significantly different for bioelectricity and bioethanol in the way that one unit of bioelectricity can be converted to more mechanical work than one unit of bioethanol. Thus the "net" impact of bioenergy systems on GHG emissions depends on the choice of reference systems, that is, the fossil-based counterparts that bioenergy systems replace and the choice of functional units, that is, on what basis the two pathways are compared. Figure 3a compares potential emissions offsets of bioethanol derived from switchgrass replacing gasoline. Approximately 53.6 g CO_2-eq GHG emissions can be saved if fossil-based gasoline is replaced by switchgrass-based bioethanol, ranging from 37.5 to 63.2 g CO_2-eq, on a per unit energy content (MJ) basis. The potential GHG offsets are roughly equivalent to a 60 % reduction in life cycle emissions.

Figure 3b compares bioelectricity derived from switchgrass with its fossil-based counterparts, electricity produced from coal-fired power generation, and electricity from the average US grid. Potential GHG offsets from replacing coal-fired electricity by bioelectricity are approximately 272.4 g CO_2-eq/MJ, or a 91 % reduction. If the reference system is the average US grid, approximately 151.9 g CO_2-eq/MJ of GHG emissions could be offset from replacing with bioelectricity, equivalent to an 84 % reduction of life cycle emissions. Although the bioethanol pathway generally implies more life cycle GHG emissions than the bioelectricity pathway (Fig. 1a), potential GHG offsets from bioelectricity are much higher than those from bioethanol on a per unit energy content basis due to different reference systems.

Figure 3c compares switchgrass bioenergy pathways with their fossil-based counterparts on a per unit area of cropland basis, a functional unit used by previous studies (e.g., Heller et al. 2003). Our results agree with previous research that the bioelectricity pathway offsets more GHG emissions than the bioethanol pathway does on a per unit area of cropland basis. This result holds true regardless of the choice of references for the bioelectricity pathway. On average, the bioelectricity pathway can potentially offset 5.9 or 13.9 tons CO_2-eq/ha-yr more GHG emissions than the bioethanol pathway can if replacing the average US grid electricity or coal-fired electricity, respectively.

Figure 3d shows the comparison of swithchgrass bioenergy pathways using vehicle kilometer traveled as the functional

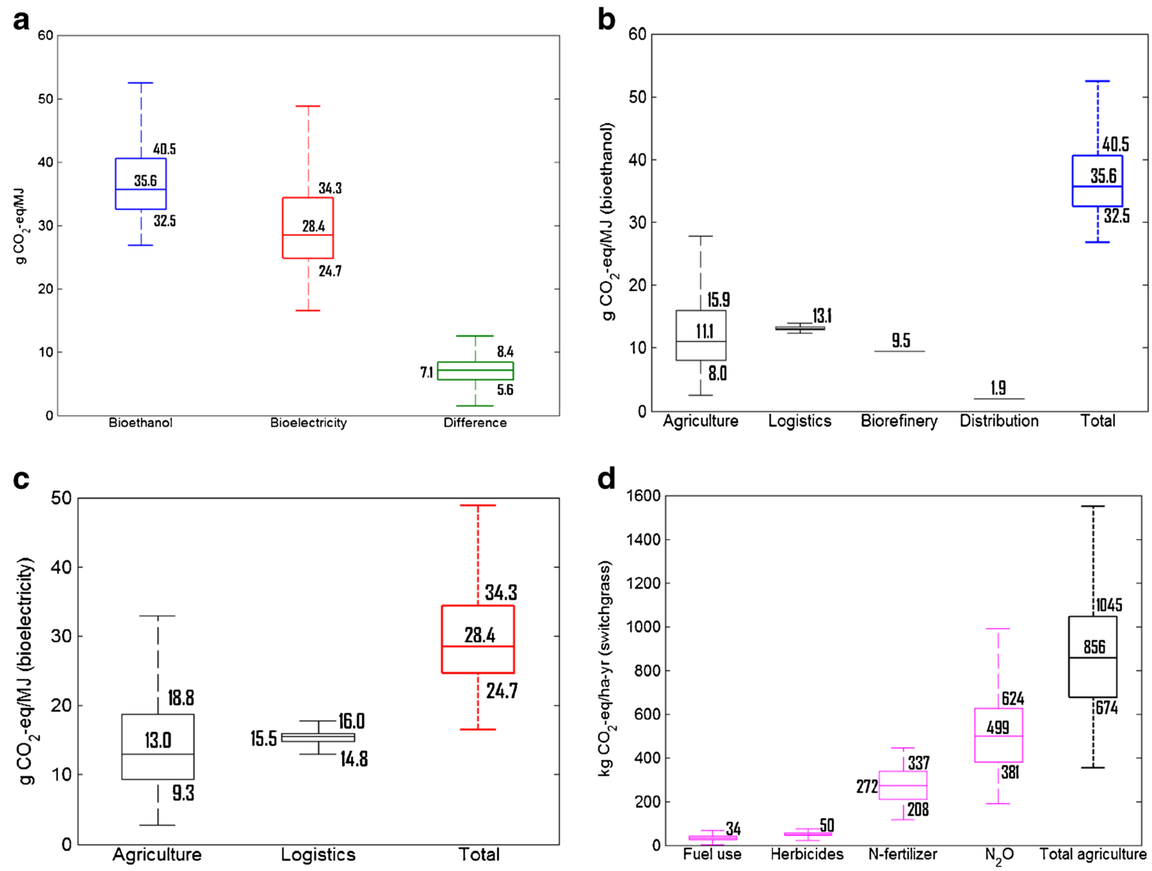

Fig. 2 Life cycle GHG emissions of switchgrass-based bioenergy: **a** comparative results on an energetic basis, **b** bioethanol by processes, **c** bioelectricity by processes, and **d** agricultural components on a per hectare basis. *Lines* in each box represent median values of each output variable, with *top lines* as the 75th percentiles and *bottom lines* as the 25th percentiles. The end of whiskers represents minimum and maximum values of each output variable excluding outliers

unit, including the vehicle cycle. Life cycle GHG emissions for per vehicle kilometer traveled using bioethanol are estimated using the fuel economy of ethanol driven FFVs at twenty miles per gallon (mpg) (Kumar and Sokhansanj 2007). Similarly, life cycle GHG emissions of gasoline on a per vehicle kilometer traveled basis are estimated using the average life cycle GHG emissions of gasoline (West et al. 2007) and the fuel economy of gasoline powered FFVs at 25 mpg (Kumar and Sokhansanj 2007). The results show that approximately 142.4 g CO_2-eq/km GHG emissions could be offset if fueling FFVs using bioethanol instead of gasoline, ranging from 100.8 to 164.0 g CO_2-eq/km. Potential GHG offsets on a per vehicle kilometer traveled basis for bioelectricity are estimated using emissions of the average US grid, average emissions of coal-fired power generation in the USA in 2009 (EPA 2012), and the fuel economy of Nissan LEAF electric car (Humbird et al. 2011). Using the average US grid electricity as the reference, bioelectricity can potentially offset 70.6 g CO_2-eq/km GHG emissions, which are less than the potential offsets offered by bioethanol. If replacing average coal-fired electricity, bioelectricity could offset approximately 157.2 g CO_2-eq/km GHG emissions which are a little bit more than what bioethanol could offset.

Given that the potential GHG offset of bioelectricity highly depends on the energy mix of the regional grid, we compare GHG offset potentials of bioethanol fueling FFVs and bioelectricity powering EVs on a per vehicle kilometer traveled basis in each of the 26 NERC subregions (Peterson and Haase 2009). As shown in Table S3, bioethanol-fueled FFVs offer more GHG offsets than bioelectricity-powered EVs do in all NERC subregions. In general, bioethanol is less favored in regions with “dirtier grid”, such as the Rocky Mountain Power Area (RMPA) than in regions with “cleaner grid”, such as Northeast Power Coordinating Council/Upstate New York (NYUP). Davis et al. (Davis et al. 2008) indicate that switchgrass yields are characteristically low in the Western USA. Therefore, although there might exist large differences in GHG offsets in western NERC subregions (e.g., NWPP and CAMX), the amount of switchgrass that can be grown and thus the amount of switchgrass-based bioenergy that can be produced in these regions are relatively marginal. Also note that the spatial variations related to switchgrass agriculture are

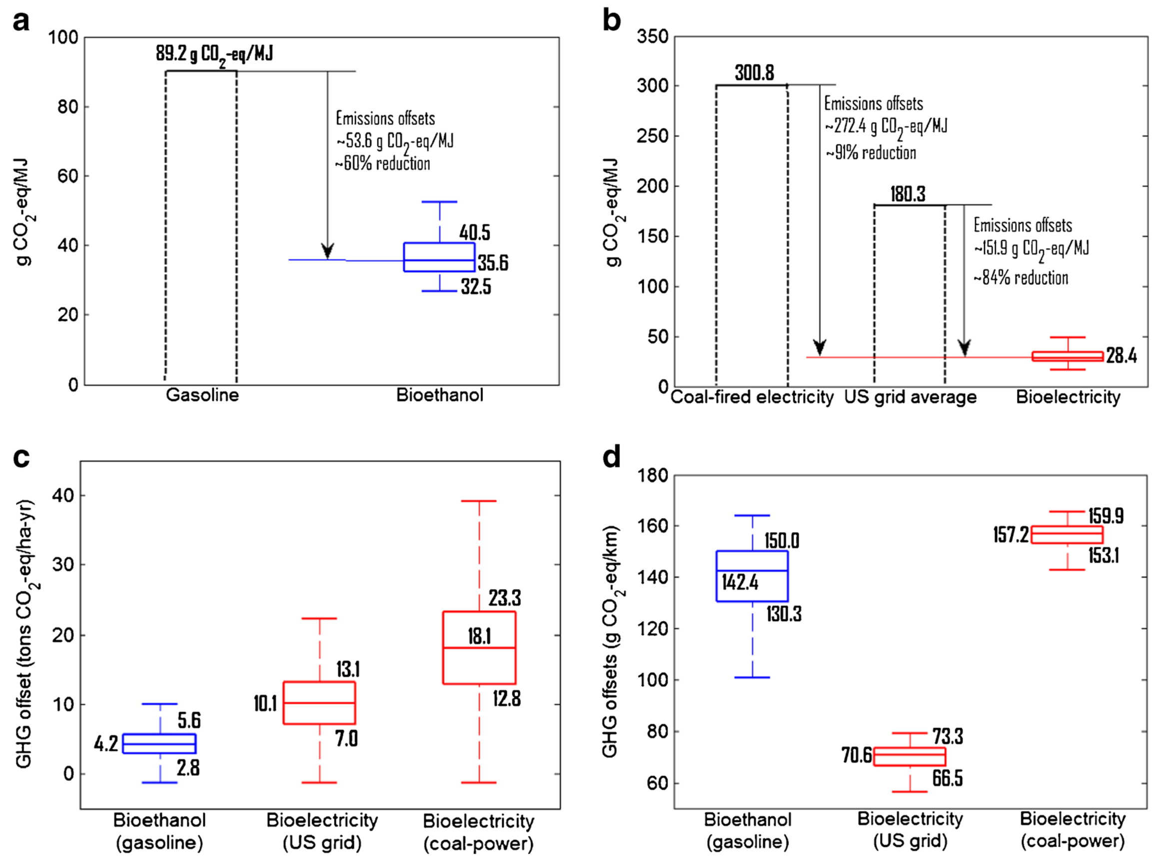

Fig. 3 Life cycle GHG offsets of switchgrass-based bioenergy: **a** offsets of bioethanol replacing gasoline on a per megajoule basis, **b** offsets of bioelectricity replacing the coal-fired electricity and the average US grid electricity on a per megajoule basis and offsets of bioethanol and bioelectricity replacing their fossil-based counterparts (*in parentheses*), **c** on a per unit area of cropland basis, and **d** on a per vehicle kilometer traveled basis including emissions from the vehicle cycle

not considered in this research, although it represents an interesting avenue for future study.

3.3 Uncertainty and sensitivity analysis

Uncertainties of the life cycle GHG analysis results for the two bioenergy pathways in our study are derived from probability distributions of key parameters. We examine the sensitivity of the result—difference of life cycle GHG emissions of bioethanol and bioelectricity—to these distributions. The results of the sensitivity analysis found that the difference of life cycle GHG emissions is most sensitive to the means of distributions of five parameters including mass fraction of cellulose in switchgrass, mass fraction of xylan in switchgrass, conversion efficiency of IGCC system, heating value of switchgrass (Fig. 4), and switchgrass yield (Fig. S8, Electronic Supplementary Material). Increasing mass fractions of cellulose and xylan in switchgrass and decreasing IGCC conversion efficiency and switchgrass heating value can make the bioelectricity pathway produce more life cycle GHG emissions than the bioethanol pathway do. In addition, switchgrass yield can dramatically change the variation of the life cycle GHG emission difference between the two pathways, but not necessarily the mean value of the result. Whereas switchgrass composition (i.e., fractions of cellulose and xylan) are constrained to fairly small ranges, switchgrass yield is both highly variable and uncertain. Switchgrass yield can be affected by geography, soil type, precipitation, and management practices. Each of these factors contributes to a large range of viable switchgrass yields. In addition to variability arising from geographic heterogeneity, yields are also uncertain. Switchgrass is not currently cultivated as a commodity crop, and many of the yield predictions are based on extrapolation of controlled field experiments. This suggests the results of this study may have regional variation according to actual switchgrass yields. Finally, it is reasonable to expect that IGCC conversion efficiency will improve over time, resulting in similar trends of the initial analysis. The comparison results do not change very much when changing the means of other parameters (Figs. S8 and S10, Electronic Supplementary Material), standard deviations of normally distributed parameters (Fig. S9, Electronic Supplementary Material), and upper and lower limits of

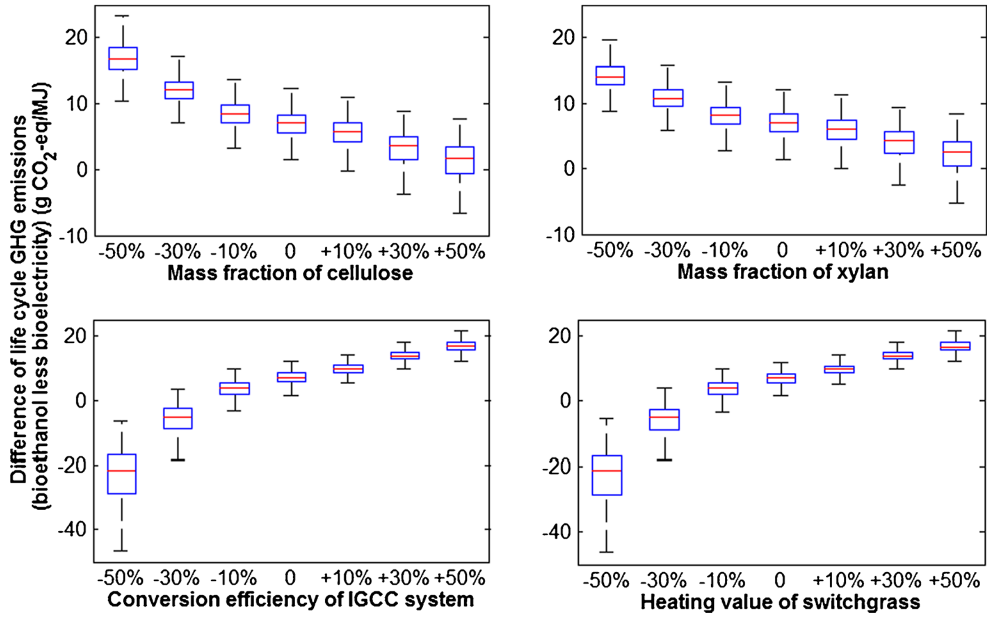

Fig. 4 Difference of life cycle GHG emissions (bioethanol less bioelectricity) after decreasing and increasing means of selected parameter distributions by 50, 30, and 10 %

triangularly distributed parameters (Fig. S11, Electronic Supplementary Material).

4 Discussion and conclusions

Our study agrees with the previous research that the bioethanol pathway generally produces more life cycle GHG emissions than the bioelectricity pathway does when compared on both a per megajoule and a per hectare basis. However, our results also show that, when compared as a function of vehicle miles traveled, the two pathways are comparable with marginal differences. In particular, using bioelectricity to replace grid power for EVs offsets fewer life cycle GHG emissions than using bioethanol to fuel FFVs in all of the 26 NERC subregions. This implies that, in regions with "cleaner" (cleaner means lower GHG emissions) grids, producing electricity from cellulosic biomass could only offer marginal GHG reduction, whereas cellulosic bioethanol becomes more promising to reduce life cycle GHG emissions. Despite the fact that the life cycle GHG emissions of bioethanol are higher than those of bioelectricity using the same feedstock, the potential GHG reduction of these two bioenergy pathways highly depends on the choice of reference system and the regional specifics of the reference system. Therefore, comparative LCA of bioenergy systems is most useful for decision support only when it is spatially explicit to address regional specifics and differences. Moving forward, the difference of GHG offsets from bioethanol and bioelectricity will change as the grid evolves. Based on the reference case in the EIA Annual Energy Outlook 2012 (EIA 2012), which covers only CO_2 emissions instead of GHG emissions, bioethanol will offer more CO_2 offsets than bioelectricity in all NERC subregions on a per vehicle kilometer traveled basis (Fig. S13, Electronic Supplementary Material). In particular, bioethanol will offer more CO_2 offsets than bioelectricity in all subregions as grids in these subregions become cleaner. After 2015, the difference of CO_2 offsets from the two bioenergy pathways stays relatively stable, except in Midwest Reliability Council/East (MROE)—most of Wisconsin and the Upper Peninsula of Michigan—where bioethanol becomes increasingly more favorable as the grid evolves. In general, when the grids get cleaner over time, the favorability of bioethanol for GHG offsets increases. However, this time-dependent comparison does not account for potential efficiency increase of gasoline combustion, which may decrease the offsets of bioethanol.

Note that this time-dependent comparison does not account for potential efficiency improvements of vehicles, which may decrease the GHG offsets of bioethanol. This is a complex issue out the scope of this study, but represents an interesting avenue for future research.

In addition to the selection of reference systems, the choice of functional units reflects stakeholder interests and can significantly impact the comparison of GHG offset potentials for bioenergy pathways. The comparison in Figs. 4 and S13 (Electronic Supplementary Material) is made from a consumption perspective using per vehicle kilometer traveled as the functional unit. In other words, the provision of vehicle kilometer traveled using bioenergy is the main consideration. On the other hand, switchgrass produced from per unit area of cropland becomes the functional unit when the utilization of feedstock to produce bioenergy is the main concern. From this production point of view, the bioethanol pathway can potentially provide more GHG offsets than the bioelectricity pathway using either the average US grid or coal-fired power generation as the reference system.

Due to variations of feedstock agriculture, technology specifics, and logistics, there are significant uncertainties associated with comparative life cycle GHG analysis of bioenergy systems. In this research, we capture uncertainties associated with the life cycle of switchgrass-based bioethanol and bioelectricity. However, we only use estimates from government databases (ANL 2012; DOE 2012; Peterson and Haase 2009) as reference systems (i.e., life cycle GHG emissions of gasoline used, US grid, and coal-fired power generation) to represent the industry average. This is sufficient for the particular purpose of this research that is to show the importance of reference and functional unit in comparative life cycle GHG analysis of bioenergy systems. When decisions are to be made, however, higher resolution data should be collected to address regional specifics of the reference system and uncertainties associated with it. Other factors such as cost (Fig. S12, Electronic Supplementary Material) should be taken into account in a multi-criteria decision analysis framework. Moreover, the system boundaries of this study only consider the life cycle GHG emissions of the production of cellulosic bioethanol and bioelectricity. The GHG emissions associated with vehicle life cycle (e.g., processing of materials, manufacturing, distribution, operation, maintenance, and end-of-life) are not taken into account. Extending system boundaries in future work can obtain additional information for the comparative assessment of both biomass pathways.

Our study demonstrates that the reference and functional unit can significantly change bioenergy pathway choices. The comparative LCA of bioenergy systems is most useful for decision support only when it is spatially explicit to address regional specifics and differences. The difference of GHG offsets from bioethanol and bioelectricity will change as the grid evolves. When the grids get cleaner over time, the favorability of bioethanol for GHG offsets increases.

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